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# Enhancing Entrepreneurship Performance Through Artificial Intelligence Technology: Evidence from Manufacturing Firms in South-West, Nigeria

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**Abstract**

This study examines how South-West Nigerian manufacturing companies' entrepreneurial success may be improved by artificial intelligence (AI) technology. The study examines the connections between AI constructs—adoption, applications, relevance, and utilization—and performance outcomes, such as competitive advantage, customer satisfaction, operational efficiency, total quality management, and innovation capability, using a sample of 346 businesses and data analysis tools like SmartPLS and SPSS. The results show that although AI adoption by itself does not considerably boost performance, competitive advantage, customer happiness, and operational efficiency are greatly impacted by AI's strategic use and applicability. The findings highlight the importance of focused AI applications in providing quantifiable advantages, especially in operational and customer-facing fields. The necessity of matching AI activities with organizational objectives is shown by the fact that AI relevance also appears as a critical component that has a beneficial influence on customer satisfaction and competitive positioning.

**Keywords:** *AI adoption, AI adoption utilization, competitive advantage, customer satisfaction, operational efficiency, SmartPLS and SPSS*

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**Background to the Study**

Artificial intelligence can be regarded as man-made intelligence built or planted in a machine that allows it to reason and function as a human being. Artificial Intelligence (AI) is a component of Industry 4.0 technologies that enhance the use of intelligent machines to perform the duties of a staff (human being) in business ventures. AI assists both potential and existing entrepreneurs in achieving operational and financial performance effectively and efficiently. Artificial intelligence (AI) refers to machines trained to perform tasks associated with human intelligence, interpret external data, learn from that external data, and use that learning to adapt to tasks to achieve specific outcomes flexibly (Shepherd & Majchrzak, 2022). Arakpogun et al. (2021) described Artificial intelligence (AI) as a collection of information communication technologies (ICTs) that imitate human intelligence for the primary purpose of improving jobs, creating greater efficiencies, and driving economic growth. Similarly, Arakpogun et al. (2021) and Miller (2019) added that AI comprises intelligent agents and intelligent systems, which enable organizations to carry out intelligent and cognitive activities that integrate the business process with tasks and enable organizations to be innovative.

As a subset of industry 4.0 technologies, AI can improve entrepreneurship performance in various aspects of the service and manufacturing industry. It is useful in performing some dangerous activities with the aid of robots or robotic machines to safeguard the lives of human beings while achieving organizational objectives. It can also function effectively with the support of the Internet of Things (IoT). IoT is the connectivity of machine to machine with a computer device that enables the connected machines to communicate effectively. Using AI in business is about automating tasks, enhancing human capabilities, and making informed decisions. From decision-making to information retrieval, AI has the potential to streamline processes and make computer interfaces more user-friendly. Its application in business spans various aspects, easing workloads and offering new avenues for innovation and efficiency (Stevany & Novia, 2023**).** It must be noted that many firms from diverse sectors increasingly apply artificial intelligence (AI) in terms of advanced data analytics and intelligent algorithms for replacing human work in selected processes (Davenport & Ronanki, 2018; Dubé et, 2018; Agrawal et al., 2018; Plastino & Purdy, 2018).

The introduction of AI technologies enables an organization to improve employee efficiency with access to a knowledge database. Also, by exploring existing knowledge, an organization continues to generate new knowledge from business processes and employee interactions (Femi et al, 2022). Artificial intelligence enables employees to access valuable information via technology-driven platforms. It is a tool that can be used or manipulated by entrepreneurs for productive activities that provide a great impact on humanity. The application of Artificial Intelligence enables firms to gain a competitive advantage and achieve superior performance due to different knowledge bases and unique intelligence planning. Organizational or entrepreneurial performance can be expressed from the operational and financial perspectives, directly impacting organizational competitiveness and strategies. While the operational perspective focuses more on the organizational success factors such as processes management and overall quality control that led to the long-term competitive edge, the financial perspective comprises the organization's financial position or statements, that is, assets and liabilities, income and expenditure as well as how revenues are generated in the organization.

Lichtenthaler (2019) suggests an intelligence-based view of firm performance as an extension of the knowledge-based and resource-based views. An intelligence-based perspective underscores the need to integrate AI applications with specific human expertise to complicate imitation by competitors. Companies must develop meta-intelligence to dynamically renew and recombine their intelligence architecture with multiple human and artificial intelligence types to sustain a competitive advantage over time. However, despite AI applications globally, there is a gap in the literature regarding its effective implementation in enhancing business performance. Although previous studies have focused on implementing AI in various sectors and its role in business process management. Nevertheless, there is a lack of comprehensive research on the various forms of its uses to enhance entrepreneurial performance. Therefore, this study creates awareness of the existence of different applications and uses of AI among entrepreneurs. It aims to offer valuable insights into how businesses can harness the power of AI to enhance their operations i.e. quality control financial planning. Similarly, robotics machines, i.e. reactive machines with limited memory, theory of mind, and self-awareness, as well as computer vision, which comprises image recognition, machine vision, and related applications, can enhance entrepreneurial performance.

**Statement of Research Problem**

A large body of literature has documented that enterprises that adopt digital technology aided by AI enhance their competitive advantage and productivity, improve customer purchasing decisions, boost operational efficiency, raise trade sales, and lower costs (Amesho et al., 2022; Anuj et al., 2021; Basri, 2020; Belhadi et al., 2021; Burian, 2021; Chan et al., 2019; Davenport & Ronanki, 2018; Grover et al., 2020; Jabłonska & Polkowski, 2017; Rai et al., 2019; Ulas, 2019; Ulrich et al., 2021; Yulia & Wamba, 2022). More recent studies have also confirmed that firms that implement AI applications are expected to boost the respective enterprises' dynamic capabilities by leveraging technology to meet new types of demand, move at speed to pivot business operations, and thus, reduce their business risks (Arzikulov, 2021; Buer et al., 2021; Burian, 2020; Dwivedi et al., 2021; Gualdi & Cordella, 2021; Kaplan & Haenlein, 2020; Nishant et al., 2020).

Despite prior evidence acknowledging the beneficial effects of AI on entrepreneurship performance, there is a remarkable lack of sufficient statistical evidence to support the assertions. Besides, there is a noticeable dearth of empirical research on AI and entrepreneurship in Nigeria. Much research on the subject focused on a systematic literature review incorporating qualitative research design and anecdotal analysis. The implication is that the results of earlier studies are inconclusive, and drawing clear-cut conclusions may also be difficult, leaving a lacuna to be filled. Realizing these gaps in the extant literature, the current study seeks to provide a more comprehensive investigation of the effect of AI on entrepreneurship performance in the Nigerian manufacturing sectors to obtain empirically robust results.

**Research Questions**

This study seeks to address the following research questions:

i. How does AI affect the competitive advantage of the enterprises in the study area?

ii. How does AI affect customer satisfaction of the enterprises in the study area?
iii. How does AI affect the operational efficiency of the enterprises in the study area?
iv. How does AI affect the total quality management of the enterprises in the study area?
v. How does AI affect the innovation capabilities of the enterprises in the study area?

**Aim and Objectives of the Study**

The primary aim of this research is to empirically explore the effect of AI as an enhancer of entrepreneurs on entrepreneurship performance in the Nigerian manufacturing sectors in the southwest region. The objectives of the study are as follows:

i. Investigate the effect of AI on the competitive advantage of the enterprises in the study area.
ii. Examine the effect of AI on the customer satisfaction of the enterprises in the study area.
iii. Evaluate the effect of AI on the operational efficiency of the enterprises in the study area.
iv. Determine the effect of AI on the total quality management of the enterprises in the study area.
v. Find the effect of AI on the innovation capabilities of the enterprises in the study area.

**Research Hypotheses**

This study postulates that:

i. AI has no significant effect on the competitive advantage of the enterprises in the study area.
ii. AI has no significant effect on the customer satisfaction of the enterprises in the study area.
iii. AI has no significant effect on the operational efficiency of the enterprises in the study area.
iv. AI has no significant effect on the total quality management of the enterprises in the study area.
v. AI has no significant effect on the innovation capabilities of the enterprises in the study area.

## Literature Review

### Historical Evolution of Entrepreneurship and Artificial Intelligence

The historical evolution of entrepreneurship has deep roots in the emergence of trade and commerce throughout ancient civilizations. While entrepreneurship has existed in various forms for centuries, the Industrial Revolution marked a transformative period. Entrepreneurs like Josiah Wedgwood and Richard Arkwright played pivotal roles in mechanizing production processes, shifting economies from agrarian to industrial (Shepherd & Majchrzak, 2022). The 19th century witnessed the rise of industrial titans such as Andrew Carnegie and John D. Rockefeller, symbolizing entrepreneurship's role in the rapid economic development of the time (Desai, 2019). This era laid the foundation for entrepreneurial principles centered on innovation, capital investment, and market expansion.

### The Emergence and Development of Artificial Intelligence

The historical trajectory of Artificial Intelligence (AI) began in the mid-20th century with foundational contributions from scholars like Alan Turing and the Dartmouth Conference in 1956 (Meena et al., 2022). The initial decades of AI research were characterized by ambitious goals and expectations, leading to the development of expert systems and symbolic AI. However, the field faced challenges and underwent "AI winters" during reduced funding and unmet expectations (Russell & Norvig, 2010). The late 20th century and early 21st century witnessed a resurgence in AI capabilities, driven by breakthroughs in machine learning, neural networks, and computational power (LeCun et al., 2015). This resurgence laid the groundwork for integrating AI into various domains, including entrepreneurship.

### Convergence of Entrepreneurship and AI in the Digital Age

The convergence of entrepreneurship and AI gained momentum in the 21st century, with entrepreneurs increasingly adopting AI technologies to drive innovation and competitiveness. The digital age saw the rise of tech startups that leveraged AI for data analytics, personalized user experiences, and automation (Chhabra et al., 2017). Entrepreneurs embraced AI as a strategic tool for decision-making, market analysis, and efficiency improvement. Integrating AI in entrepreneurial ventures transformed business models, creating new opportunities and challenges (D'Mello et al., 2022). This historical evolution showcases the intertwined paths of entrepreneurship and AI, with the digital age positioning AI as a fundamental driver of innovation and economic growth in entrepreneurial activities.

### Entrepreneurship

Entrepreneurship is a dynamic and multifaceted concept involving identifying, creating, and pursuing opportunities to establish or transform new ventures. Shane and Venkataraman (2000) articulated that entrepreneurship is an individual's willingness to take risks, innovate, and mobilize resources to bring novel ideas, products, or services to the market. It is a process that demands creativity, proactiveness, and adaptability in navigating uncertainties. Entrepreneurship goes beyond the mere initiation of businesses; it involves recognizing opportunities, creating value, and contributing to economic and social development.

Entrepreneurship is pivotal in modern business, driving economic development, innovation, and job creation. In the globalized and rapidly evolving business environment, entrepreneurs act as catalysts for change, introducing novel ideas, products, and services that contribute to the overall dynamism of economies. Shane and Venkataraman (2000) highlight that entrepreneurship involves identifying and exploiting opportunities, and entrepreneurs are instrumental in transforming innovative concepts into tangible ventures. The capacity of entrepreneurs to take calculated risks, navigate uncertainties, and adapt to market demands fosters resilience and agility within economies. Furthermore, entrepreneurship is recognized for its role in promoting competition, which, in turn, stimulates efficiency, productivity, and continuous improvement across industries (Audretsch&Thurik, 2001).

In addition to economic impact, entrepreneurship is a vital source of job creation and employment. A study by the Global Entrepreneurship Monitor (GEM) emphasizes the substantial role of entrepreneurs in job generation, particularly in small and medium-sized enterprises (SMEs) (Reynolds et al., 2005). Entrepreneurs contribute to reducing unemployment rates by creating new job opportunities, fostering a dynamic labor market, and fostering an environment conducive to skill development. This job creation is essential for individual economic well-being and contributes to communities' social and economic fabric. Overall, the importance of entrepreneurship in the contemporary business landscape extends beyond financial gains, encompassing its profound impact on economic growth, innovation, and societal well-being (Anokhin, Schulze, 2009).

**Entrepreneurship Performance**

Entrepreneurship performance is a comprehensive measure of the outcomes and success of entrepreneurial activities. It encompasses financial achievements, innovation, job creation, and societal impact. Audretsch and Keilbach (2004) emphasize that financial performance metrics such as revenue growth, profitability, and return on investment are crucial to entrepreneurship success. Innovation performance assesses the entrepreneur's ability to introduce new products, services, or processes, contributing to market differentiation. Job creation reflects the economic impact of entrepreneurship, indicating the generation of employment opportunities. Entrepreneurship performance is a holistic evaluation of how entrepreneurs leverage their skills, resources, and opportunities to achieve their goals and contribute to economic development (Raharjo et al., 2023).

**Artificial Intelligence (AI)**

Artificial Intelligence (AI) is a field of computer science that focuses on creating systems capable of performing tasks that typically require human intelligence. As Russell and Norvig (2010) defined, AI involves the development of algorithms and models that enable machines to exhibit cognitive functions such as learning, problem-solving, and decision-making. Machine learning, a subset of AI, allows systems to improve their performance based on experience without being explicitly programmed. AI technologies encompass a range of applications, including natural language processing, computer vision, and robotics, offering transformative potential across various industries (Kumar, et al., 2023).

**Machine Learning (ML)**

Machine learning is a subset of artificial intelligence that involves the development of algorithms allowing systems to learn from data and make predictions or decisions without being explicitly programmed. ML has significant implications for predictive analytics, customer segmentation, and decision-making in entrepreneurship. Entrepreneurs can utilize ML algorithms to analyze vast datasets, identify patterns, and make data-driven predictions, aiding in market trend analysis and strategic planning (Pallathadkaet al., 2023). ML's ability to adapt and improve its performance over time makes it a powerful tool for entrepreneurs seeking to optimize various aspects of their ventures.

**Natural Language Processing (NLP)**

Natural Language Processing involves the interaction between computers and human language. In entrepreneurship, NLP technologies enable machines to understand, interpret, and generate human-like text. Entrepreneurs leverage NLP for sentiment analysis in customer feedback, chatbots for customer service, and extracting valuable insights from textual data (Pallathadkaet al., 2023). By automating language-related tasks, entrepreneurs can enhance customer communication, streamline internal processes, and gain deeper insights into market perceptions and trends.

**Computer Vision**

Computer vision enables machines to interpret and make decisions based on visual data, a capability akin to human vision. In entrepreneurship, computer vision has transformative potential in image recognition, augmented reality, and quality control. Entrepreneurs can use computer vision to automate visual inspection processes in manufacturing, develop innovative products using augmented reality applications, or enhance user experiences in e-commerce through image recognition technologies (Weber et al., 2023). These applications improve operational efficiency and contribute to innovation and differentiation in entrepreneurial ventures.

**Role of Artificial Intelligence (AI) in Enhancing Entrepreneurship Performance**

Artificial Intelligence (AI) has emerged as a transformative force in enhancing entrepreneurship performance across various domains. AI technologies, including machine learning, natural language processing, and data analytics, provide entrepreneurs with powerful tools to analyze vast datasets, identify patterns, and make informed decisions. As Mikalef et al. (2023) noted, AI can significantly improve the efficiency of business processes, enabling entrepreneurs to streamline operations, optimize resource allocation, and enhance overall productivity. Moreover, AI-driven automation allows entrepreneurs to delegate routine tasks, freeing up valuable time for strategic decision-making and creative problem-solving (Ahmad et al., 2023).

The role of AI in entrepreneurship extends beyond operational efficiency to innovation and market competitiveness. Entrepreneurs leverage AI to gain insights into consumer behavior, preferences, and market trends, aiding in developing tailored products and services (Sharma et al., 2023). AI-driven innovations also play a crucial role in enhancing customer experiences through personalized interactions and efficient customer service. Dabbous and Boustani (2023) highlight that integrating AI technologies empowers entrepreneurs to stay ahead of the competition by fostering agility and adaptability in response to dynamic market conditions. By harnessing the potential of AI, entrepreneurs can not only optimize their existing ventures but also explore novel avenues for growth and differentiation in the highly competitive business landscape.

**Revolutionizing Decision-Making**

Artificial Intelligence (AI) has revolutionized decision-making processes within entrepreneurial endeavours. The analytical capabilities of AI, particularly in machine learning, empower entrepreneurs to sift through vast datasets and extract valuable insights. This data-driven decision-making approach enhances strategic planning and risk management for entrepreneurs (Choudhary et al., 2020). Studies have shown that adopting AI technologies significantly improves the quality and speed of decision-making in entrepreneurial contexts, contributing to more informed and effective choices (Lacity & Willcocks, 2017).

Entrepreneurs harness the power of AI-driven data analytics to make informed decisions. Machine learning algorithms analyze vast datasets, providing valuable insights into market trends, consumer behaviors, and competitive landscapes. This data-driven decision-making is crucial for entrepreneurs seeking a competitive edge in dynamic markets (Braganza et al., 2022). Studies by Ali and Frimpong (2020) highlight the transformative impact of AI on decision-making processes, allowing entrepreneurs to anticipate market shifts and adapt their strategies accordingly. Advancements in machine learning, natural language processing, and computer vision collectively impact entrepreneurship by significantly enhancing decision-making processes. With machine learning's predictive capabilities, entrepreneurs can make informed decisions based on data analysis (Schmitt, 2023). Natural language processing allows for the efficient analysis of textual data, providing entrepreneurs with valuable insights from customer reviews, social media, and market reports. Computer vision enables entrepreneurs to interpret visual data, aiding in quality control, product innovation, and user interface design. Integrating these technologies into decision-making processes empowers entrepreneurs to navigate complexities and uncertainties in the business landscape.

**Enhancing Operational Efficiency**

The impact of AI on entrepreneurship is particularly evident in operational efficiency. Automation facilitated by AI technologies minimizes manual intervention in routine tasks, enabling entrepreneurs to optimize processes and allocate resources more efficiently (Brynjolfsson & McAfee, 2014). This increased efficiency directly impacts cost savings and improved productivity, providing entrepreneurs a competitive advantage in their respective industries. Research suggests that integrating AI into operational workflows substantially increases efficiency and resource utilization for entrepreneurial ventures (Arora et al., 2016). Entrepreneurs increasingly leverage AI technologies for operational automation, streamlining routine tasks, and enhancing efficiency. This includes automating data entry, customer support, and inventory management. AI-driven automation reduces entrepreneurs' workload and contributes to cost savings and resource optimization (Bouteet al., 2022). Research by Bhimaet al. (2023) emphasizes how automation through AI enhances productivity and operational efficiency, freeing up time for entrepreneurs to focus on strategic decision-making.

**Fostering Innovation and Market Adaptability**

AI catalyzes innovation, offering entrepreneurs the tools to adapt to rapidly changing market conditions. By utilizing machine learning algorithms, entrepreneurs gain insights into consumer behaviors and market trends, allowing for more informed and agile decision-making (Allioui &Mourdi, 2023). This adaptability is crucial for entrepreneurial ventures seeking to stay ahead in dynamic and competitive markets. Studies emphasize that AI's role in fostering innovation contributes significantly to the market adaptability of entrepreneurial ventures, positioning them for sustained growth ((Allioui & Mourdi, 2023).

AI is a driving force behind innovation in product development for entrepreneurs. Entrepreneurs leverage AI for product design, prototyping, and optimization tasks. Machine learning algorithms can analyze market trends and consumer feedback to inform the development of new and improved products (Venkateswaran et al., 2014). This application of AI in innovation contributes to the agility of entrepreneurial ventures, allowing them to respond quickly to changing customer demands and industry trends (Venkateswaran et al., 2014).

**Addressing Challenges and Unleashing New Opportunities**

While the impact of AI on entrepreneurship is transformative, it comes with challenges that entrepreneurs must navigate. Among the concerns are ethical considerations, data security, and the potential for job displacement (Chesbrough & Brunswicker, 2013). However, integrating AI also presents new entrepreneurial opportunities, with ventures emerging to address challenges associated with AI adoption. Entrepreneurs exploring AI development, consulting, or niche applications within AI-driven industries find new avenues for business growth (Tiwana et al., 2010). The dynamic interplay of challenges and opportunities underscores the profound impact of AI on the entrepreneurial landscape.

**Personalization of Customer Experiences**

Entrepreneurs utilize AI technologies to personalize customer experiences, tailoring products, services, and marketing strategies to individual preferences. Natural Language Processing (NLP) and machine learning algorithms analyze customer data, enabling entrepreneurs to offer personalized recommendations and targeted marketing campaigns (Sikka et al., 2024). This personalization enhances customer satisfaction and contributes to customer loyalty and retention, factors critical for the success of entrepreneurial ventures in competitive markets.

**Theoretical Review**

The relevant theories for this study include resource-based, innovation diffusion and dynamic capabilities theory. Each theory has its strengths and weaknesses with different ideological bases, as explained below:

**The Resource-Based View (RBV)**

The Resource-Based View (RBV): The Resource-Based View provides a theoretical lens to understand how firms can leverage resources, including AI technologies, to enhance entrepreneurship performance. According to Barney (1991), valuable, rare, inimitable, and non-substitutable resources can lead to sustained competitive advantage. In the context of entrepreneurship, the integration of AI technologies becomes a critical resource. The RBV suggests that firms deploying AI for tasks such as data analysis, decision-making, and automation can gain a competitive edge, ultimately influencing entrepreneurship performance positively. Technology Acceptance Model (TAM): The Technology Acceptance Model, developed by Davis (1989), focuses on user perceptions and attitudes towards technology adoption. TAM can be applied to understand how entrepreneurs perceive and adopt AI technologies in the context of entrepreneurship and AI. The model suggests that perceived ease of use and perceived usefulness significantly impact an individual's intention to use a particular technology. Applying TAM to entrepreneurship performance through AI involves assessing entrepreneurs' attitudes towards AI, their perceptions of its usability, and the extent to which they believe AI contributes to enhancing their performance (Al-Adwan et al., 2023).

**Innovation Diffusion Theory**

Rogers' (1962) Innovation Diffusion Theory provides insights into the adoption and spread of innovations within a social system. In entrepreneurship and AI, this theory helps explain how AI technologies disseminate and become integrated into entrepreneurial practices. The theory identifies innovators, early adopters, and the mainstream majority as distinct adopter categories. Entrepreneurs at different stages of the diffusion process may experience varying impacts on their performance. Understanding the diffusion dynamics of AI in entrepreneurship provides a nuanced perspective on the time-sensitive nature of technology adoption and its implications for entrepreneurship performance.

**Dynamic Capabilities Theory**

The Dynamic Capabilities Theory, as proposed by Teece (1997), focuses on a firm's ability to adapt and reconfigure its resources in response to changing environments. In entrepreneurship and AI, dynamic capabilities are crucial for leveraging AI technologies effectively. Entrepreneurs need to continually sense, seize, and transform their strategies and operations to capitalize on the potential of AI. This theoretical framework suggests that the agility and adaptability of entrepreneurs in integrating and evolving with AI technologies contribute significantly to entrepreneurship performance in dynamic and competitive business landscapes (DaneshvarKakhki et al., 2023).

**Methodology**

This section introduces the methodology adopted to carry out the study. The fundamental aspect includes carefully considering the selection process for the research design to eliminate bias, as it may affect the results. The procedure covers the study population, sample and sampling technique, a detailed description of the survey instruments, the validity and reliability of instruments, and data analysis methods.

**Research Design**

An online cross-sectional survey research design was employed to explore how AI technology enhances entrepreneurship performance among manufacturing firms in south-west Nigeria. The central objective of this survey is to collect necessary information from larger samples at a single time to answer the research questions and select appropriate techniques to test hypotheses to enlarge a better understanding of the subject matter. In addition, an online survey is a cost-effective method to reach out to many participants with minimum effort and cost. If designed appropriately, online surveys help collect data related to multiple variables using a single data collection instrument (Fuldeore & Soliman, 2017). Primary data were collected through electronic questionnaires administered to SMEs' technical AI executives who can offer insight into the impact of AI and analytical operations in manufacturing firms. At the same time, the canonical regression technique was employed for statistical analysis.

**Population, Sample and Sampling Technique**

Thirty-three thousand five hundred and eighty-four (18,216) registered manufacturing enterprises in Ekiti, Lagos, Ogun, Ondo, Osun, and Oyo states (Corporate Affairs Commission survey, 2023) constitute the target population for this study. The enterprises are those under manufacturing business categories. The sector was chosen because it contributes significantly to the national GDP (NBS, 2023). Field survey revealed that Ekiti has 1,399 registered enterprises, Lagos has 5,067 enterprises, Ogun has 3,837 enterprises, Ondo has 2,445 enterprises, Osun has 1786 enterprises, and Oyo has 3,682 enterprises, respectively. The unit of analysis comprises top technical executives in charge of AI functions in each firm. A 3-stage sampling technique is adopted for the research sample selection. The stages comprise purposive, quota and simple random sampling techniques. Purposive sampling is used in the first stage to select manufacturing business categories and states to be studied. Four manufacturing firms' categories, namely, long-term digitalization process, technology solution, and data-driven transformation, were selected for the study. At the same time, four out of the six states in the Southwest region were selected. Consequently, this study is limited to Lagos, Ogun, Ondo and Oyo because of homogeneity characteristics among the states with a total population size of fifteen thousand and thirty-one (15,031). The second stage of the sampling technique involves proportionate stratified sampling based on enterprises' categories and selected states' contribution to the target population. In the final stage, the sample units are drawn using a simple random sampling technique. The use of this sampling technique is to give every member of the population a chance to be selected and to reduce bias to the barest minimum. In estimating the sample size for this study, Krejcie and Morgan (1970) was employed where:

$$n = \frac{Z^2\alpha/_2 \times N \times \sigma^2}{e^2(N-1) + Z^2\alpha/_2\,\sigma^2}$$

N = population size

n = sample size

e = acceptable margin of error or the precision or the estimation error

$\sigma$ = standard deviation of the population

$Z\alpha/_2$ = the value of the standard variate at a given confidence level.

Based on the model, three hundred and seventy-four (374) enterprises are adequate for a population size of fifteen thousand and thirty-one (15,031) at a margin error of 5% and p-value of 0.5 with a predetermined critical value of 1.96.

**Survey Instrument, Validity and Reliability**

An online survey questionnaire with closed-ended questions is the research instrument used to gather the study's primary data on a five-point rating scale. The instrument is administered to technical AI executives in the manufacturing firms in Lagos, Ogun, Ondo and Oyo states. The online surveying method allows the participants to attempt the survey at a convenient time and place (Hatchison et al., 2014). In addition, it provides the ability to gather much information from a large sample within a very short period and ensure the anonymity of the participants, contributing to the greater reliability of the answers. At the beginning of the survey, the instrument was designed in English and accompanied by a cover letter to introduce the research focus and instructions to be followed by the respondents. At the same time, electronic administration was conducted from 20th September 2024 to 20th October 2024. For this purpose, e-mail addresses of the manufacturing companies were randomly generated in advance using the CAC database (2023). 374 companies were contacted by e-mail, WhatsApp and phone calls and requested to participate in the survey; only three and fifteen (315) responses were received, which showed that eighty-four percent (84%) of the respondents attempted and returned the 3-section online questionnaires. The first section comprises the demographic characteristics to identify the participants' background information, such as age, gender, employment status, job category, job rank, academic qualifications and experience in using AI technology. The second section included questions about the adoption, implementation and usage of AI technology in manufacturing enterprises. The next section followed a query about entrepreneurship performance in terms of competitive advantage, customer satisfaction, operational efficiency, total quality management, and innovation capabilities.

Face, content and construct validity were deployed to check if the questionnaire measured what it intended to measure. The instrument's reliability was achieved through the use of Cronbach's Alpha to measure the instrument's internal consistency. At the same time, the normality of the sampled data is computed using multivariate Kurtosis. Furthermore, exploratory factor analysis (EFA) is deployed to evaluate the unidimensionality and factor-analysis ability of the identified constructs.

**Method of Data Analysis, Model Specification and Ethical Consideration**

Descriptive and inferential statistics are utilized in the analysis of data. Descriptive statistical tools include frequency, percentage, mean, standard deviation, skew and kurtosis. At the same time, the canonical regression model (CRM) is employed as an inferential statistical tool to test the degree of relationship between AI technology and entrepreneurship performance in the Nigerian manufacturing sectors in the southwest region.

**Model Specification**

The study model is specified as follows:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + u \ldots\ldots (1)$$

**Where:**

$y_{1\text{-}5}$ = Entrepreneurship performance (competitive advantage, customer satisfaction, operational efficiency, total quality management, innovation capabilities)

$y_{1=}$Competitive advantage

$y_{2=}$Customers satisfaction

$y_{3=}$Operational efficiency

$y_{4=}$Total quality management

$y_{5=}$Innovation capabilities

$\beta_0$= Intercept

$\beta_1$ = Parameter associated with $x_1$
$\beta_2$ = Parameter associated with $x_2$
$\beta_3$ = Parameter associated with $x_3$
$x_1$ = AIT adoption
$x_2$ = AIT level of usage
$x_3$ = AIT implementation
u = The error term or disturbance.
Therefore, the model becomes:
Entrepreneurship performance$_i$ = $\beta_0$ + $\beta_1$AIT adoption + $\beta_2$AIT level of usage +$\beta_3$AIT implementation + $u$..........................................................................................(2)

**Challenges and Ethical Considerations**
While these innovations offer tremendous opportunities for entrepreneurship, they also bring challenges and ethical considerations. Entrepreneurs must grapple with issues such as data privacy, algorithm bias, and the ethical use of AI technologies (Ahmad et al., 2023). Striking a balance between harnessing the potential of these advancements and addressing associated challenges is crucial for responsible and sustainable entrepreneurial practices in the AI era.

**Analysis and Findings**
**Respondents Profile**
The respondent profile shows varied demographic distribution (Table 1), offering important insights into South-West Nigerian manufacturing enterprises' workforce and entrepreneurial environment. Most responders (39.3%) are between the ages of 20 and 25, with those between the ages of 26 and 35 coming in second (27.7%). This suggests a primarily young workforce, essential for using cutting-edge technology like artificial intelligence (AI). The gender distribution reveals a notable preponderance of male participation (85%), which is consistent with the gender dynamics frequently seen in Nigeria's industrial sector. The majority of respondents (35.5%) are married, according to the marital status statistics, but the participants' varied living situations are highlighted by the significant number of single people (24.9%), divorced people (19.1%), and widowed people (20.5%).

The analysis reveals a fairly balanced distribution of years of experience about professional experience and education. A total of 44% have between 11 and 25 years of experience, 15% have fewer than 10 years, and 20.5% have more than 25 years. This combination of younger and more experienced workers puts the industry in a position to combine cutting-edge AI technology with conventional knowledge. The industry mostly employs people with mid-level education, as seen by the educational credentials biased towards Diploma/NCE holders (70.5%) and Degree/HND holders (25.7%). This educational profile highlights the necessity for focused AI training programs to upskill staff members for improved entrepreneurial success.

The business attributes highlight the region's predominance of small businesses (67.3%), with medium-sized businesses making up 32.7%. Ownership arrangements are dominated by partnerships (30.1%) and sole proprietorships (42.5%), which reflects the entrepreneurial spirit that propels these companies. Most businesses (25.7%) have been in business for five to ten years and are well-represented across all age groups. These results point to a stable but expanding industry ready for new ideas. Adopting AI technology might be a game-changer for many businesses, allowing them to make better decisions, optimize processes, and perform better in competitive and shifting market conditions.

**Table 1:** Respondents Profile

| Demographic | | Frequency | Percent |
|---|---|---|---|
| Age | Below 20 years | 55 | 15.9 |
| | 20 – 25 years | 136 | 39.3 |
| | 26 - 35 years | 96 | 27.7 |
| | 36 – 50 years | 46 | 13.3 |
| | 51 – 60 years | 8 | 2.3 |
| | Above 60 years | 5 | 1.4 |
| | Total | 346 | 100.0 |
| Gender | Male | 294 | 85.0 |
| | Female | 52 | 15.0 |
| | Total | 346 | 100.0 |
| Marital Status | Married | 123 | 35.5 |
| | Single | 86 | 24.9 |
| | Divorced | 66 | 19.1 |
| | Widowed | 71 | 20.5 |
| | Total | 346 | 100.0 |
| Year of Experience | Above 25 years | 71 | 20.5 |
| | 21 – 25 years | 86 | 24.9 |
| | 16 – 20 years | 66 | 19.1 |
| | 11 – 15 years | 71 | 20.5 |
| | Below 10 years | 52 | 15.0 |
| | Total | 346 | 100.0 |
| Highest Educational Qualification | No education | 7 | 2.0 |
| | Technical School | 3 | 0.9 |
| | Diploma/NCE | 244 | 70.5 |
| | Degree/HND | 89 | 25.7 |
| | Postgraduate degree | 3 | 0.9 |
| | Total | 346 | 100.0 |
| Business classification | Small scale | 233 | 67.3 |
| | Medium scale | 113 | 32.7 |
| | Total | 346 | 100.0 |
| Years of Firm in Operation | Less than 5 years | 72 | 20.8 |
| | 5 – 10 years | 89 | 25.7 |
| | 11 – 15 years | 66 | 19.1 |
| | 16 – 29 years | 68 | 19.7 |
| | Above 30 years | 51 | 14.7 |
| | Total | 346 | 100.0 |
| Business Ownership Status | Sole – proprietorship | 147 | 42.5 |
| | Partnership | 104 | 30.1 |
| | Private limited liability company | 39 | 11.3 |
| | Cooperative societies | 56 | 16.2 |
| | Total | 346 | 100.0 |

### Preliminary Analysis

Certain preliminary analyses were carried out for this study to ensure the collected data was clean. Multicollinearity, heteroskedasticity, and normality tests were performed on the gathered data. When a study's independent variables are highly linked, multicollinearity is present, which might provide inaccurate results (Kothari & Garg, 2014). In order to check for multicollinearity, the Variance Inflation Factor (VIF) was employed in this investigation.

### Normality Test

As Tabachnick and Fidell (2013) recommended, examining the graphical distribution in a study with a sample size of 200 or more is crucial. This study also used the graphical technique to assess the data's normality. The regression normalized residual histogram was employed, and Fig. 1 showed that all of the histogram's bars were traveling in the direction of the histogram's center. This demonstrates that the presumption of normalcy is upheld.

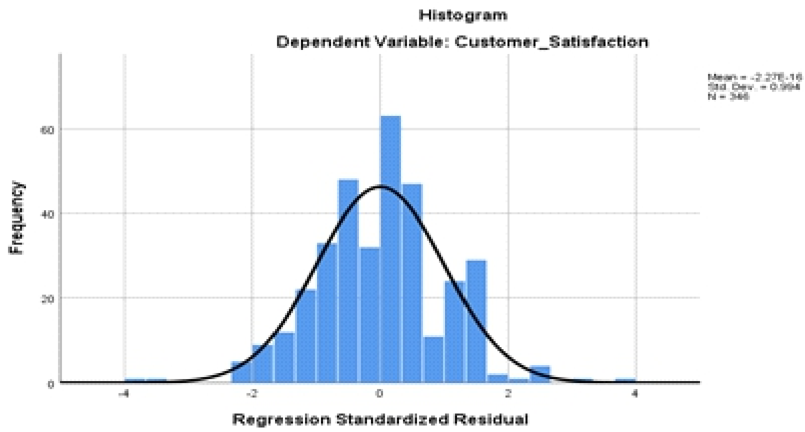



**Figure 1:** Histogram

### Multicollinearity Test

Using regression findings produced by SPSS, the multicollinearity test was conducted using the Variance Inflation Factor (VIF) and the tolerance value. According to Marcoulides and Raykov (2019), multicollinearity across variables is present when the tolerance level is 0.20 or less or when the VIF value is 5 or higher (refer to Table 2).

**Table 2:** Tolerance Value and VIF

| Variables | Collinearity Statistics | |
|---|---|---|
| | Tolerance | VIF |
| AI Adoption | 0.787 | 1.270 |
| AI technology Utilization | 0.844 | 1.185 |
| AI Relevance | 0.578 | 1.731 |
| AI Applications | 0.613 | 1.631 |

### Heteroskedasticity Test

The absence of heteroskedasticity is one of the regression model's traditional presumptions. To determine if heteroskedasticity is present in a model or not, several methods may be applied. For this investigation, the scatterplot graph approach is used. Figure 2 displays the scatterplot graph between the residual (SRESID) and the independent variable predictive values (ZPRED). It is evident from the scatterplot's output in Figure 2 that the spots do not offer a distinct pattern. Therefore, it can be said that the regression model is not affected by the heteroskedasticity issue.

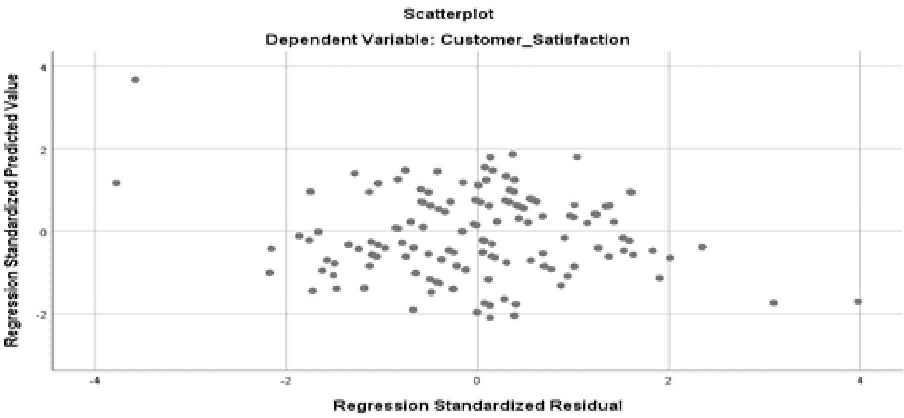



**Figure 2:** Scatterplot Graph

**Descriptive Statistics of the Variables**

Table 3's descriptive statistics provide important information about the latent variables affecting the performance of entrepreneurs using artificial intelligence (AI) technology in South-West Nigerian manufacturing companies. The deployment of AI technology is generally prevalent among organizations, as seen by the relatively high mean score (3.47) and moderate standard deviation (SD = 0.82), with replies displaying considerable consistency. AI technology utilization scores, on the other hand, are noticeably lower (Mean = 2.40, SD = 0.69), indicating a substantial gap between acceptance and efficient use of AI technologies that may limit their potential advantages. The variables AI applications (Mean = 3.25, SD = 1.05) and AI relevance (Mean = 3.24, SD = 0.90) show moderate attitudes, indicating that businesses acknowledge the value and applicability of AI but may encounter implementation difficulties because of differences in their comprehension and use.

With the greatest mean score (3.95) and the lowest variability (SD = 0.67), operational efficiency stands out among the results, indicating that the integration of AI has greatly enhanced operational procedures. AI helps with strategic positioning and quality enhancements, as seen by the high scores for competitive advantage (Mean = 3.47, SD = 0.63) and overall quality management (Mean = 3.75, SD = 0.93). On the other hand, customer satisfaction performs moderately (Mean = 3.11, SD = 0.93), suggesting that more AI may be used to improve customer-centric operations. Lastly, while the variability indicates varying degrees of influence among organizations, innovation capability (Mean = 3.76, SD = 1.02) shows promise as an area where AI fosters creativity and flexibility. To fully realize AI's disruptive potential in entrepreneurial performance, these findings highlight the necessity of improving its use and coordinating its adoption with strategic objectives.

**Table 3:** Descriptive Statistics of Latent Variable

| | Mean | Std. Deviation |
|---|---|---|
| AI Adoption | 3.4721 | 0.82319 |
| AI technology Utilization | 2.4020 | 0.69183 |
| AI Relevance | 3.2447 | 0.90290 |
| AI Applications | 3.2512 | 1.05441 |
| Competitive Advantage | 3.4754 | 0.63671 |
| Customer Satisfaction | 3.1112 | 0.93408 |
| Operational Efficiency | 3.9533 | 0.67560 |
| Total Quality Management | 3.7464 | 0.93565 |
| Innovation Capability | 3.7619 | 1.02199 |

**Correlations of Variables**

The correlation table sheds light on the connections between factors related to AI technology and the success of entrepreneurs in South-West Nigerian manufacturing companies. High adoption rates may not necessarily translate into effective usage or relevance, as indicated by the negative association between AI adoption and both AI technology utilization (-0.387, $p < 0.01$) and AI relevance (-0.257, $p < 0.01$). This discrepancy emphasizes the need to strategically coordinate AI adoption procedures with operational requirements to guarantee its applicability and efficiency. On the other hand, AI applications exhibit a strong positive correlation with both customer satisfaction (0.662, $p < 0.01$) and AI relevance (0.620, $p < 0.01$), suggesting that using AI in particular applications improves customer-focused outcomes and highlights its usefulness in promoting entrepreneurial performance.

Furthermore, the significance of AI in generating strategic and innovative advantages for businesses is shown by the positive and substantial correlations between AI relevance, competitive advantage (0.433, $p < 0.01$), and innovation capability (0.116, $p < 0.05$). Operational efficiency displays substantial positive associations with AI relevance (0.265, $p < 0.01$) and AI applications (0.288, $p < 0.01$), showing AI's contribution to simplifying operations. It is interesting to note that overall quality management does not significantly correlate with most factors. This suggests that, although AI adoption affects other aspects of performance, its effects on quality management procedures could need further research or focused efforts. Together, these results show how adopting AI presents both possibilities and obstacles, underscoring the significance of deliberate deployment to fully realize AI's transformational potential in boosting entrepreneurial success.

**Table 4:** Correlations of Variables

| | AI Adoption | AI technology Utilization | AI Relevance | AI Applications | Competitive Advantage | Customer Satisfaction | Operational Efficiency | Total Quality Management | Innovation Capability |
|---|---|---|---|---|---|---|---|---|---|
| AI Adoption | | | | | | | | | |
| AI technology Utilization | -.387** | | | | | | | | |
| AI Relevance | -.257** | 0.032 | | | | | | | |
| AI Applications | -.122* | 0.033 | .620** | | | | | | |
| Competitive Advantage | -.119* | 0.018 | .433** | .476** | | | | | |
| Customer Satisfaction | -.188** | 0.042 | .612** | .662** | .475** | | | | |
| Operational Efficiency | 0.003 | -0.014 | .265** | .288** | .316** | .207** | | | |
| Total Quality Management | -0.036 | -0.045 | 0.027 | 0.014 | 0.063 | 0.037 | 0.019 | | |
| Innovation Capability | -0.045 | -0.040 | 0.045 | 0.048 | .116* | 0.037 | -0.026 | .588** | |

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

## Measurement Model Evaluation

Partial least squares (PLS) analysis of the study model was performed using Smar-tPLS 3.0 software (Ringle et al., 2015). Drawing on the two-stage analytical methodologies proposed by Ramayah, Yeap, and Ignatius (2013), the study examines the measurement model before moving on to the structural model. The bootstrapping approach evaluated the route coefficients and loadings for significance (Hair et al., 2017). In particular, the study evaluated the measurement model's discriminant and convergent validity.

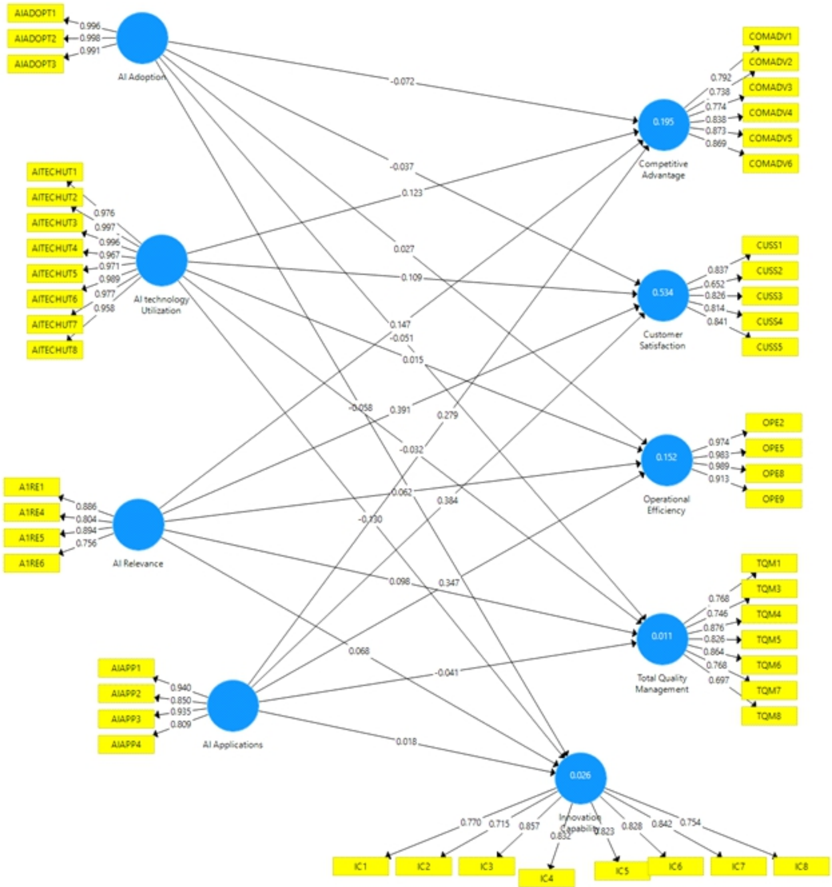
## Convergent validity

The loadings determined convergent validity, average variance extracted (AVE), and composite reliability (Hair et al., 2017). Table 5 and Figure 2 show that each build achieves loadings over 0.7. Additionally, all constructions' composite reliability (CR) is greater than 0.7, and their AVE is above 0.5, as Hair et al. (2014) advised. Convergent validity is therefore attained in this investigation.

**Table 5:** Convergent validity

| Constructs | Items | Loadings | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|---|
| AI Adoption | AIADOPT1 | 0.996 | 0.997 | 0.990 |
| | AIADOPT2 | 0.998 | | |
| | AIADOPT3 | 0.991 | | |
| AI Relevance | A1RE1 | 0.886 | 0.903 | 0.700 |
| | A1RE4 | 0.804 | | |
| | A1RE5 | 0.894 | | |
| | A1RE6 | 0.756 | | |
| AI Applications | AIAPP1 | 0.940 | 0.935 | 0.783 |
| | AIAPP2 | 0.850 | | |
| | AIAPP3 | 0.935 | | |
| | AIAPP4 | 0.809 | | |
| AI technology Utilization | AITECHUT1 | 0.976 | 0.995 | 0.958 |
| | AITECHUT2 | 0.997 | | |
| | AITECHUT3 | 0.996 | | |
| | AITECHUT4 | 0.967 | | |
| | AITECHUT5 | 0.971 | | |
| | AITECHUT6 | 0.989 | | |
| | AITECHUT7 | 0.977 | | |
| | AITECHUT8 | 0.958 | | |
| Competitive Advantage | COMADV1 | 0.792 | 0.922 | 0.665 |
| | COMADV2 | 0.738 | | |
| | COMADV3 | 0.774 | | |
| | COMADV4 | 0.838 | | |
| | COMADV5 | 0.873 | | |
| | COMADV6 | 0.869 | | |
| Customer Satisfaction | CUSS1 | 0.837 | 0.896 | 0.636 |
| | CUSS2 | 0.652 | | |
| | CUSS3 | 0.826 | | |
| | CUSS4 | 0.814 | | |
| | CUSS5 | 0.841 | | |
| Innovation Capability | IC1 | 0.770 | 0.936 | 0.646 |
| | IC2 | 0.715 | | |
| | IC3 | 0.857 | | |
| | IC4 | 0.832 | | |
| | IC5 | 0.823 | | |
| | IC6 | 0.828 | | |
| | IC7 | 0.842 | | |
| | IC8 | 0.754 | | |
| Operational Efficiency | OPE2 | 0.974 | 0.982 | 0.932 |
| | OPE5 | 0.983 | | |
| | OPE8 | 0.989 | | |
| | OPE9 | 0.913 | | |
| Total Quality Management | TQM1 | 0.768 | 0.923 | 0.631 |
| | TQM3 | 0.746 | | |
| | TQM4 | 0.876 | | |
| | TQM5 | 0.826 | | |
| | TQM6 | 0.864 | | |
| | TQM7 | 0.768 | | |
| | TQM8 | 0.697 | | |

**Figure 3:** Measurement Model




## Discriminant Validity HTMT Ratio

Because it is regarded as a reliable metric for evaluating discriminant validity, the HTMT ratio was examined (Henseler et al., 2015). The HTMT criteria show that discriminant validity is achieved in this investigation. Only none of the correlations is above the acceptable range of 0.85, as shown in Table 6 (Henseler et al., 2015).

**Table 6:** Heterotrait-Monotrait Ratio

| | AI Adoption | AI Applications | AI Relevance | AI technology Utilization | Competitive Advantage | Customer Satisfaction | Innovation Capability | Operational Efficiency | Total Quality Management |
|---|---|---|---|---|---|---|---|---|---|
| AI Adoption | 0.995 | | | | | | | | |
| AI Applications | -0.121 | 0.885 | | | | | | | |
| AI Relevance | -0.214 | 0.665 | 0.837 | | | | | | |
| AI technology Utilization | -0.161 | 0.111 | 0.010 | 0.979 | | | | | |
| Competitive Advantage | -0.158 | 0.400 | 0.349 | 0.167 | 0.815 | | | | |
| Customer Satisfaction | -0.185 | 0.660 | 0.655 | 0.162 | 0.432 | 0.797 | | | |
| Innovation Capability | -0.054 | 0.056 | 0.091 | -0.118 | 0.121 | 0.050 | 0.804 | | |
| Operational Efficiency | -0.031 | 0.386 | 0.287 | 0.050 | 0.312 | 0.268 | 0.018 | 0.965 | |
| Total Quality Management | -0.062 | 0.026 | 0.081 | -0.027 | 0.070 | 0.051 | 0.542 | 0.045 | 0.795 |

## Structural Model Assessment

The structural model results in Table 7 reveal significant insights into the relationships between AI-related constructs and entrepreneurship performance dimensions in manufacturing firms in South-West Nigeria. Surprisingly, AI adoption does not significantly predict any of the performance outcomes, as evidenced by non-significant p-values across all relationships, including competitive advantage ($\beta = -0.072$, $t = 1.224$, $p = 0.222$), customer satisfaction ($\beta = -0.037$, $t = 1.049$, $p = 0.295$), and innovation capability ($\beta = -0.058$, $t = 0.939$, $p = 0.348$). This suggests that adopting AI technology without focusing on strategic or operational alignment does not guarantee improved performance outcomes. These findings underline the necessity of moving beyond adoption to ensure relevance, effective utilization, and targeted applications of AI.

AI applications, however, demonstrate significant positive effects on several key outcomes. The relationship between AI applications and competitive advantage ($\beta = 0.279$, $t = 5.171$, $p = 0.000$), customer satisfaction ($\beta = 0.384$, $t = 7.367$, $p = 0.000$), and operational efficiency ($\beta = 0.347$, $t = 5.064$, $p = 0.000$) are strongly supported. These results highlight that applying AI in specific, targeted areas significantly enhances organizational competitiveness, customer satisfaction, and process efficiency. However, AI applications do not significantly influence innovation capability ($\beta = 0.018$, $t = 0.258$, $p = 0.796$) or total quality management ($\beta = -0.041$, $t = 0.486$, $p = 0.627$), suggesting that the benefits of AI applications are more pronounced in external-facing outcomes than internal quality or creativity enhancements.

AI relevance shows a mixed influence, with significant positive relationships with competitive advantage ($\beta = 0.147$, $t = 2.423$, $p = 0.016$) and customer satisfaction ($\beta = 0.391$, $t = 6.810$, $p = 0.000$). These results underscore the importance of ensuring AI relevance to organizational goals and customer needs to achieve strategic and satisfaction-related outcomes. However, AI relevance does not significantly predict innovation capability ($\beta = 0.068$, $t = 0.951$, $p = 0.342$), operational efficiency ($\beta = 0.062$, $t = 0.993$, $p = 0.321$), or total quality management ($\beta = 0.098$, $t = 1.080$, $p = 0.281$). This indicates that while relevance enhances competitiveness and customer experiences, it may not strongly influence internal capabilities or operational metrics (Figure 3).

Lastly, AI technology utilization shows a nuanced influence. It significantly predicts competitive advantage ($\beta = 0.123$, $t = 2.597$, $p = 0.010$), customer satisfaction ($\beta = 0.109$, $t = 2.989$, $p = 0.003$), and innovation capability ($\beta = -0.130$, $t = 2.085$, $p = 0.038$). The positive impact on competitive advantage and customer satisfaction highlights that effective utilization of AI drives tangible benefits. Interestingly, the negative relationship with innovation capability suggests potential inefficiencies or misalignments in how AI is utilised to foster innovation. However, AI technology utilization does not significantly affect operational efficiency ($\beta = 0.015$, $t = 0.301$, $p = 0.763$) or total quality management ($\beta = -0.032$, $t = 0.463$, $p = 0.643$), pointing to areas where utilization practices may require refinement for broader organizational impact.

**Table 7:** Results of the structural model

| Relationship | β | Standard Deviation (STDEV) | t-value | p-value | Decision |
|---|---|---|---|---|---|
| AI Adoption -> Competitive Advantage | -0.072 | 0.059 | 1.224 | 0.222 | Not Supported |
| AI Adoption -> Customer Satisfaction | -0.037 | 0.036 | 1.049 | 0.295 | Not Supported |
| AI Adoption -> Innovation Capability | -0.058 | 0.062 | 0.939 | 0.348 | Not Supported |
| AI Adoption -> Operational Efficiency | 0.027 | 0.048 | 0.571 | 0.568 | Not Supported |
| AI Adoption -> Total Quality Management | -0.051 | 0.074 | 0.695 | 0.487 | Not Supported |
| AI Applications -> Competitive Advantage | 0.279 | 0.054 | 5.171 | 0.000 | Supported |
| AI Applications -> Customer Satisfaction | 0.384 | 0.052 | 7.367 | 0.000 | Supported |
| AI Applications -> Innovation Capability | 0.018 | 0.071 | 0.258 | 0.796 | Not Supported |
| AI Applications -> Operational Efficiency | 0.347 | 0.069 | 5.064 | 0.000 | Supported |
| AI Applications -> Total Quality Management | -0.041 | 0.085 | 0.486 | 0.627 | Not Supported |
| AI Relevance -> Competitive Advantage | 0.147 | 0.061 | 2.423 | 0.016 | Supported |
| AI Relevance -> Customer Satisfaction | 0.391 | 0.057 | 6.810 | 0.000 | Supported |
| AI Relevance -> Innovation Capability | 0.068 | 0.071 | 0.951 | 0.342 | Not Supported |
| AI Relevance -> Operational Efficiency | 0.062 | 0.062 | 0.993 | 0.321 | Not Supported |
| AI Relevance -> Total Quality Management | 0.098 | 0.090 | 1.080 | 0.281 | Not Supported |
| AI technology Utilization -> Competitive Advantage | 0.123 | 0.047 | 2.597 | 0.010 | Supported |
| AI technology Utilization -> Customer Satisfaction | 0.109 | 0.036 | 2.989 | 0.003 | Supported |
| AI technology Utilization -> Innovation Capability | -0.130 | 0.062 | 2.085 | 0.038 | Supported |
| AI technology Utilization -> Operational Efficiency | 0.015 | 0.051 | 0.301 | 0.763 | Not Supported |
| AI technology Utilization -> Total Quality Management | -0.032 | 0.068 | 0.463 | 0.643 | Not Supported |

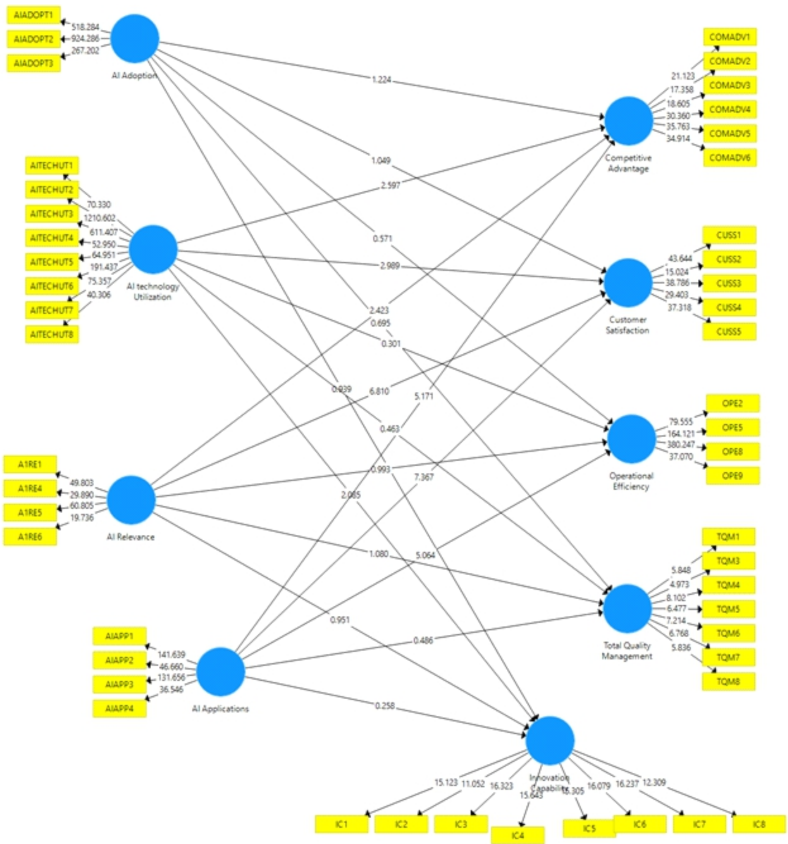



**Figure 4:** Structural Model

## R Square

The percentage of variance in the dependent variables that can be accounted for by the independent variables—AI Adoption, AI Technology Utilization, AI Relevance, and AI Applications—is shown by the R-square values in Table 8. With an R-square of 0.534, Customer Satisfaction has the best explanatory power, indicating that the independent variables explain more than 53% of its variation. With R-squares of 0.195 and 0.152, respectively, competitive advantage and operational efficiency are modestly explained, suggesting that the independent variables make smaller but significant contributions. On the other hand, the weak explanation of Innovation Capability (R-square: 0.026) and Total Quality Management (R-square: 0.011) suggests that the independent variables have little effect on these results.

**Table 8:** R Square

| | R Square | R Square Adjusted |
|---|---|---|
| Competitive Advantage | 0.195 | 0.186 |
| Customer Satisfaction | 0.534 | 0.528 |
| Innovation Capability | 0.026 | 0.014 |
| Operational Efficiency | 0.152 | 0.142 |
| Total Quality Management | 0.011 | -0.001 |

## Effect-size ($f^2$)

The unique contributions of AI Adoption, AI Applications, AI Relevance, and AI Technology Utilization to the explained variation of each dependent variable are displayed by the impact size (f2) values in Table 9. Customer satisfaction ($f^2 = 0.173$) and operational efficiency ($f^2 = 0.078$) are the areas where AI applications have the biggest influence, demonstrating their importance in these domains. Additionally, AI Relevance significantly improves Customer Satisfaction ($f^2 = 0.175$), underscoring its significance in boosting this result. However, with $f^2$ values near zero, suggesting insignificant contributions, all independent factors show modest effects on Innovation Capability and Total Quality Management.

**Table 9:** Effect-size ($f^2$)

| | Competitive Advantage | Customer Satisfaction | Innovation Capability | Operational Efficiency | Total Quality Management |
|---|---|---|---|---|---|
| AI Adoption | 0.006 | 0.003 | 0.003 | 0.001 | 0.002 |
| AI Applications | 0.053 | 0.173 | 0.000 | 0.078 | 0.001 |
| AI Relevance | 0.014 | 0.175 | 0.002 | 0.002 | 0.005 |
| AI technology Utilization | 0.018 | 0.024 | 0.017 | 0.000 | 0.001 |

## Construct Crossvalidated Redundancy

The Construct Crossvalidated Redundancy ($Q^2$) values, which show how predictively relevant the independent factors are for each dependent variable, are shown in Table 10. Operational Efficiency ($Q^2 = 0.137$) and Competitive Advantage ($Q^2 = 0.125$) have moderate predictive relevance, while Customer Satisfaction ($Q^2 = 0.335$) has the highest predictive relevance. The model appears to explain relatively little variance in Innovation Capability ($Q^2 = 0.011$) and

Total Quality Management ($Q^2 = 0.001$), on the other hand, which show low predictive value.

**Table 10**: Construct Cross validated Redundancy

| | SSO | SSE | Q² (=1-SSE/SSO) |
|---|---|---|---|
| AI Adoption | 1038.000 | 1038.000 | |
| AI Applications | 1384.000 | 1384.000 | |
| AI Relevance | 1384.000 | 1384.000 | |
| AI technology Utilization | 2768.000 | 2768.000 | |
| Competitive Advantage | 2076.000 | 1816.635 | 0.125 |
| Customer Satisfaction | 1730.000 | 1149.794 | 0.335 |
| Innovation Capability | 2768.000 | 2737.452 | 0.011 |
| Operational Efficiency | 1384.000 | 1194.815 | 0.137 |
| Total Quality Management | 2422.000 | 2418.982 | 0.001 |

**Theoretical Implications**

This study makes a substantial contribution to the body of knowledge on how artificial intelligence (AI) technologies can improve the performance of entrepreneurs in South-West Nigerian manufacturing enterprises. This study explores various aspects of AI, such as its applications, relevance, and utilization, in contrast to earlier research that primarily concentrated on AI adoption alone. This allows a better understanding of how these aspects impact organizational outcomes like competitive advantage, customer satisfaction, operational efficiency, innovation capability, and overall quality management. The results show that while adopting AI has no discernible effect on the performance outcomes of entrepreneurship, its applications and relevance considerably improve customer satisfaction and competitive advantage (Mokogwu et al., 2024). The Resource-Based View (RBV), which stresses that using certain technology capabilities as strategic assets may provide a competitive advantage, is consistent with these findings (Barney, 1991).

Furthermore, by demonstrating that the usefulness and significance of AI technology go beyond simple adoption, the study has theoretical implications for the Technology Acceptance Model (TAM). The results reinforce the notion that the effectiveness of AI is contingent upon its alignment with market dynamics and organizational objectives, underscoring the significance of context-specific AI deployment tactics (Venkatesh & Davis, 2000). Additionally, the established connections between the use of AI technology and both customer satisfaction and competitive advantage support the Diffusion of Innovation (DOI) theory (Rogers, 2003), emphasizing how the adoption and integration of AI into operational frameworks have a substantial impact on outcomes that are market-oriented and customer-centric.

This study adds to the growing corpus of entrepreneurship and digital transformation research in developing nations. It proves that the benefits of AI's use are inconsistent across all performance metrics, indicating the necessity of strategically allocating priorities. The idea that technology developments must be adapted to certain organizational capacities to optimize their impact is further supported by the disparate impacts of innovation capability and operational efficiency (Adegbuyi et al., 2024; Teece et al., 1997). This study establishes a framework for future investigations into the relationship between technology, entrepreneurship, and organizational success in comparable contexts by placing AI in Nigerian manufacturing companies' particular difficulties.

**Summary**

This study, "Enhancing Entrepreneurship Performance through Artificial Intelligence Technology: Evidence from Manufacturing Firms in South-West Nigeria. The study investigates how different aspects of organizational performance, such as competitive advantage, customer satisfaction, operational efficiency, total quality management, and innovation capability, relate to AI constructs related to adoption, applications, relevance, and technology utilization. The research uses structural modeling to offer evidence-based insights into the strategic use of AI to improve entrepreneurial success. The study investigates the connections between different aspects of organizational performance, such as competitive advantage, customer satisfaction, operational efficiency, total quality management, innovation capability, and AI constructs, including adoption, applications, relevance, and technology utilization. The research intends to offer evidence-based insights into how AI might be strategically used to improve entrepreneurial success through structural modeling.

The results show that the adoption of AI alone has no discernible impact on performance outcomes. This implies that using AI technologies alone could not result in significant advancements without addressing their operational integration and strategic alignment. The study highlights that rather than just existing in businesses, the advantages of AI rely on how technology is used and incorporated into organizational procedures. These findings suggest a disconnect between the practical effects of AI on entrepreneurial performance and its adoption.

On the other hand, relevance and AI applications turned out to be powerful indicators of performance in particular domains. Applications of AI greatly increased operational effectiveness, customer happiness, and competitive advantage, highlighting the need to use AI technologies strategically and practically. Likewise, it was shown that AI relevance has a beneficial impact on customer satisfaction and competitive advantage, underscoring the need to match AI solutions to corporate goals and consumer requirements. These constructs, however, had little effect on overall quality management and innovation capabilities, suggesting possible areas for internal process optimization and creative enhancement.

The study also emphasizes the complicated link between innovation capabilities and AI technology use, which has a negative correlation but also strongly predicts competitive advantage and consumer happiness. According to this research, while efficient use of AI improves external results, misaligned or ineffective methods may stifle creativity. All things considered, the study offers insightful information on the strategic significance of integrating AI into entrepreneurship, urging attention to customized applications, operational significance, and efficient use to optimize its possible influence. These findings have real-world applications for industrial companies using AI technology for improved performance and long-term sustainability.

## Conclusion

The influence of artificial intelligence (AI) technologies on entrepreneurial success across 346 manufacturing enterprises in South-West Nigeria was investigated in this study using SmartPLS and SPSS. The results highlight that, despite its broad usage, AI does not always result in better performance outcomes. Rather, the report emphasizes how strategic AI applications and their alignment with corporate objectives are important factors that influence operational effectiveness, customer happiness, and competitive advantage. However, there are still gaps in how AI affects internal processes like innovation capabilities and overall quality control, which suggests that AI technologies must be integrated more strategically. The report highlights the significance of going beyond simple adoption and concentrating on AI's efficient use and real-world applications. Businesses are more likely to see significant gains in performance results when they match AI projects with strategic objectives and operational requirements. In order to promote entrepreneurial growth and long-term competitiveness, our findings provide managers and policymakers in the industrial sector practical insights and support customized AI policies that put relevance, applicability, and effective utilization first.

## Recommendations

1. Managers should concentrate on applying AI in particular high-impact domains, including competitive positioning, operational procedures, and customer service. According to the report, AI applications greatly improve operational effectiveness, customer happiness, and competitive advantage. Managers should identify key business processes where AI may offer instantaneous and quantifiable advantages.
2. AI projects must align with managers' organizations' strategic goals. Customizing AI tools and systems to match organizational and customer-specific demands is essential since AI relevance benefits customer satisfaction and competitive advantage. Regular evaluations should be conducted to match AI solutions with changing market demands.
3. Employees should receive training from managers on how to use AI technology efficiently. Doing this closes the gap between technology use and organizational performance, and AI technologies are guaranteed to be completely maximized. In order to increase user efficiency and acceptance, training programs must emphasize real-world, sector-specific applications.
4. By investing in strong digital infrastructure and offering financial assistance to businesses using AI technology, policymakers such as SEMEDAN should foster an atmosphere conducive to AI integration. Policies that support economic access to these technologies may fuel widespread adoption and efficient use of AI solutions.
5. Policymakers should create industry-wide standards and best practices for AI deployment to optimize the advantages of AI relevance and applications. To guarantee consistency with corporate and national economic goals, these standards should strongly emphasise AI's moral and efficient application.
6. To encourage AI-driven innovation, policymakers should help government agencies and commercial companies form collaborations. These partnerships can aid research and development projects that improve AI applications in competitive and customer-focused settings.

7. AI-related training programs and courses should be incorporated into the school curriculum to give students the information and abilities they need to use AI efficiently. For graduates to be ready for difficulties in the real world, these programs must emphasize real-world applications and case studies unique to a certain sector.
8. To create research and internship programs with an AI focus, institutions should collaborate with manufacturing companies and other sectors. By bridging the gap between academic knowledge and real-world application, this partnership can help graduates become more innovative and competent.
9. To assist startups and entrepreneurs in investigating cutting-edge AI applications, universities, colleges of education, and polytechnics might establish AI innovation centers. These centers may act as breeding grounds for fresh concepts, especially those that link AI technology to a company's competitive edge and operational effectiveness.

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